

Chapter 2

Modeling for System's Understanding

Marisa Analía Sánchez
Universidad Nacional del Sur, Argentina

ABSTRACT

The purpose of this chapter is to provide an overview of System Dynamics modeling and to highlight its potential as a tool for system's understanding. Although the work is not intended to cover all the activities involved in a simulation process, the authors present the steps in the modeling process. The authors first summarize the role of Causal Loop diagrams in the modeling process. The authors then introduce Stock-and-flow diagrams and describe how they can be defined using mathematical functions. Along this chapter the authors claim that System Dynamics is an adequate modeling tool for “partially reducible uncertainty” and “irreducible uncertainty” problems. Finally, the authors discuss that in System Dynamics, validity means adequacy with respect to a purpose, and hence it cannot be made in absolute terms and the authors briefly introduce a set of techniques for testing structure and accuracy.

INTRODUCTION

Simulation is a fascinating tool given the wide range of domains of application, the ability to include probabilistic behavior, the flexibility to describe nonlinear relationships, and the scalability for large systems. The complexities of the phenomena in the world force us to use simulation to understand much of anything about them. Complexity may arise from structural or dynamic aspects. Structural complexity refers to the number of components in a system, or the number of combinations one must consider in making a decision. In this case we face the combinatorial explosion

DOI: 10.4018/978-1-4666-4369-7.ch002

problem. In the literature there are many references to this problem which has implications on the amount of resources needed to compute solutions (Pelánek, 2008).

Dynamic complexity arises because systems are dynamic, tightly coupled, governed by feedback, nonlinear, history-dependent, self-organizing, and adaptive (Sterman, 2000). To understand dynamic complexity, consider the evolution of a population. This is a dynamic system whose rules are very simple: the population grows according to a birth rate and decreases according to a death rate. Dynamic complexity is given by the interaction of these rules. If we know the rates with some precision then we can build a model and easily study the evolution of the system over time. On the other hand, if the size of the population varies by factors relevant, but unclear, then we can build a model to test our assumptions about the system's behavior, but we can hardly use it as a forecasting tool. These observations lead us to think that there is a variety of degrees of difficulty when dealing with dynamic systems.

The level of uncertainty with regard to the behavior of a system determines the difficulty in building a model. At one extreme we have the systems whose rules are well known; for example, sales revenues can be estimated with an arbitrary degree of accuracy given enough demand data. If from the analysis of historical data we identify variables that partially explain the behavior of demand, then, we are in the presence of conditioning and unknown information. And hence model building is more challenging. Lo and Mueller analyze the role of quantitative methods in theory and practice (Lo & Mueller, 2010). Based on the classic work of Knight that distinguishes risk from uncertainty (Knight, 1921), Lo and Mueller propose a five-tiered categorization of uncertainty in any system, whether it be physical, economic, or political. The classification ranges from complete deterministic certainty (Level 1), exemplified by Newtonian mechanics, through noisy systems and those that must be described statistically because of incomplete knowledge about deterministic processes (Levels 3 or 4), to "irreducible uncertainty" (Level 5).

The level of uncertainty restricts the set of adequate modeling and analysis tools. A system with "risk without uncertainty" (Level 2) or with "fully reducible uncertainty" (Level 3), may be analyzed using classic probability theory or Monte Carlo simulation. But in the case of systems with "partially reducible uncertainty" (Level 4) or "irreducible uncertainty" (Level 5), we need a theory-building approach, such as System Dynamics.

System Dynamics modeling was developed by Jay W. Forrester and has gained relevance in recent years because of the need to model complex systems. System Dynamics postulates that the behavior of such systems results from the underlying structure of flows, delays, and feedback loops (Forrester, *Industrial Dynamics*, 1961). There is a tradition in the use of dynamic simulation to study problems in the social sciences. Currently, it is used in public health (Barlas, 2002; Horner &

22 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: www.igi-global.com/chapter/modeling-system-understanding/77797

Related Content

Application of the Cluster Analysis in Computational Paleography

Loránd Lehel Tóth, Raymond Eliza Ivan Pardede, György András Jeney, Ferenc Kovács and Gábor Hosszú (2016). *Handbook of Research on Advanced Computational Techniques for Simulation-Based Engineering* (pp. 525-543). www.irma-international.org/chapter/application-of-the-cluster-analysis-in-computational-paleography/140403

Simulation of Temperature and Precipitation under the Climate Change Scenarios: Integration of a GCM and Machine Learning Approaches

Umut Okkan and Gul Inan (2016). *Handbook of Research on Advanced Computational Techniques for Simulation-Based Engineering* (pp. 465-491). www.irma-international.org/chapter/simulation-of-temperature-and-precipitation-under-the-climate-change-scenarios/140400

On Simulation Performance of Feedforward and NARX Networks Under Different Numerical Training Algorithms

Salim Lahmiri (2016). *Handbook of Research on Computational Simulation and Modeling in Engineering* (pp. 171-183). www.irma-international.org/chapter/on-simulation-performance-of-feedforward-and-narx-networks-under-different-numerical-training-algorithms/137438

Interaction Design for Tangible Augmented Reality Applications

Gun A. Lee, Gerard J. Kim and Mark Billinghurst (2007). *Emerging Technologies of Augmented Reality: Interfaces and Design* (pp. 261-282). www.irma-international.org/chapter/interaction-design-tangible-augmented-reality/10168

Social Impact and Challenges of Virtual Reality Communities

Rafael Capilla (2011). *Virtual Technologies for Business and Industrial Applications: Innovative and Synergistic Approaches* (pp. 164-180). www.irma-international.org/chapter/social-impact-challenges-virtual-reality/43410